A comprehensive analysis on IoT based smart farming solutions using machine learning algorithms

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ABSTRACT

Agriculture and farming are the most important and basic industries that are very important to humanity and generate a considerable portion of any nation's GDP. For good agricultural and farming management, technological advancements and support are required. Smart agriculture (or) farming is a set of approaches that uses a variety of current information and communication technology to improve the production and quality of agricultural products with minimum human involvement and at a lower cost. Smart farming is mostly based on IoT technology, since there is a need to continually monitor numerous aspects in the agricultural field, such as water level, light, soil characteristics, plant development, and so on. Machine learning algorithms are used in smart farming to increase production and reduce the risk of crop damage. Data analytics has been shown through extensive study to improve the accuracy and predictability of smart agricultural systems. Data analytics is utilised in agricultural fields to make decisions and recommend acceptable crops for production. This study provides a comprehensive overview of the different methods and structures utilised in smart farming. It also provides a thorough analysis of different designs and recommends appropriate answers to today's smart farming problems.

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1. INTRODUCTION

Internet connectivity is available to more than 80% of the world's population. Random mobile contact, spot messaging, mobile phone calls, immersive two-way video chat, voice-over-internet-protocol (VoIP), social networking, and ecommerce websites are all examples of how technology has influenced modern living. The internet of things (IoT) is the future web platform for environmental and technological communication. The IoT is a cost-effective and secure technology that may be used to upgrade a variety of domains. IoT-based solutions are being developed to autonomously monitor and track farms with minimum human interaction. The IoT is a technical advancement that allows smart gadgets and machines to communicate with one another while reducing human involvement. As young people relocate to major cities, agricultural human resources are dwindling, and farmland is shrinking as a result of urbanisation. As a result, many agricultural operations will need to be simplified in order to fulfil rising food demand.

Smart farming has recently piqued the interest of many academics, since it may assist farmers in making dynamic farm and crop management decisions. The quality of agricultural goods and the lives of farmers may be considerably improved with the adoption of different new technologies in the information and communication industry. Smart farming technology is employed by approximately 80 percent of farmers in the United States, and about 24 percent of farmers in Europe. Intelligent farming enables farmers to improve, automate, and optimise conventional farming practises, resulting in improved agricultural productivity and a simpler cultivation system. Various IoT sensors are used in intelligent farming, and these sensors are connected with agricultural equipment, resulting in a synergistic rise in crop output and productive agriculture experiences.

The basic components which are essentially needed for smart farming are: i) sensors: to provide vital information regarding various farm parameters (soil moisture, water level, and fertilizer level) to do precise farming; ii) connectivity: cellular (3G/4G/5G), ZigBee, WiFi; iii) gateway: microcontrollers; iv) location: GPS; v) data analytics:R, Pandas; vi) IoT components: DeviceHive, Arduino, Raspberry PI. A typical smart farming is a four stage process as illustrated in Figure 1.

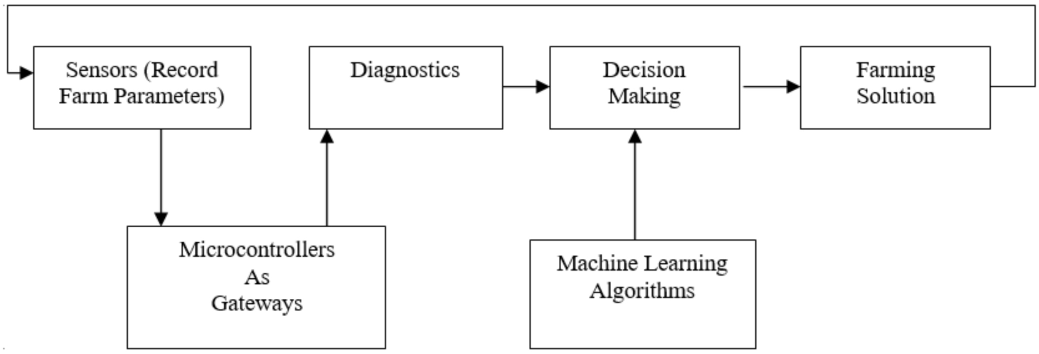


Figure 1. Basic smart farming architecture

Sensors are used to determine numerous agricultural factors that are required for a given crop, such as soil type, moisture level, nutrient presence, and so on. The readings collected from the sensors are mapped with certain criteria in order to identify the agricultural product's unique demands or inadequacies. To make intelligent judgments, machine learning algorithms are applied, and it gives a good agricultural solution. The smart farming cycle continues as a result of the reaction. The specifics of several kinds of sensors used in smart farming are shown in Table 1 (in appendix).

2. SMART FARMING SOLUTIONS BASED ON IOT AND MACHINE LEARNING APPROACHES

Rezk *et al.* [1] developed "An efficient IoT based smart farming system employing machine learning algorithms," a novel IoT-based smart farming technology. To increase crop production, they used a system dubbed WPART, which is based on a wrapper feature selection approach. In their method, they've included a powerful decision-making tool called PART. The outputs of the PART algorithm do not need any global optimization. The wrapper algorithm is used to improve the performance of the classifier. Their technique has a flaw in that it just looks at time series data and does not forecast future values. The model obtained 92.51% accurate results.

Vincent *et al*. [2] developed an expert methodology for using sensor networks to assess agricultural land suitability. The agricultural dataset was created using a variety of IoT sensors, including pH sensors, soil moisture sensors, salinity sensors, and electromagnetic sensors. Their assessment and analysis method is based on the multi-layer-perceptron (MLP). The cloud platform was used to store the data collected from the different IoT devices. The network architecture, weight correction, and activation properties all play a role in the effectiveness of this study model.

Varghese and Sharma [3] demonstrated a simple and economical IoT system for monitoring diverse crops under real-time conditions. In order to construct a low-cost intelligent agricultural module, they combined IoT and machine learning technologies. All of the agricultural data sets that are monitored have been moved to the cloud (Amazon AWS). The generated dataset is trained using logistic regression (LR) and support vector machine (SVM), which are useful for forecasting future crop conditions based on historical data. Anand *et al.* [4] created a novel model that analyses soil quality and forecasts the optimum crop type suited for cultivation in that soil. The node MCU ESP8266 microcontroller is used in their technique. The key soil data were aggregated using three primary sensors: a temperature sensor, a rain sensor, and a humidity sensor to examine its fertility and quality. The technique for obtaining environmental data was also described in their model. This information may be used to anticipate environmental conditions and aid farmers in making decisions. As a storage server, an open cloud server (ThingSpeak) is employed. A hybrid technique, which combines multiple linear regression (MLR) and K-Means clustering, is used to forecast the crop suited for cultivation in that soil.

Reddy *et al.* [5] proposed an unique smart irrigation system. To anticipate a crop's water consumption, they used a decision tree paired with several regression and classification techniques algorithm. Multiple agricultural sensors were used to create their model, which can monitor temperature, wetness, and humidity. The information acquired by the system is sent to a cloud-based IoT system. The Raspberry Pi and the DHT11 soil moisture sensor are used in their model. Truong *et al.* [6] built an IoT framework that includes sensors, an LTE HUA8372 Wi-Fi internet module, and a microcontroller. Their model can collect environmental data in real time and send it to a cloud storage service. The support-vector-machine-regression (SVMr) technique is used to detect fungal infections in a range of environments. They've also devised a method for predicting and spreading severe fungal diseases. SVMr is a popular tool for delivering intelligent solutions.

By monitoring soil moisture, soil temperature, and climatic variables, Goap *et al.* [7] established an open-source technique for identifying field-based irrigation needs using soil characteristics. The approach uses support vector regression (SVR) and k-means clustering to estimate soil moisture differences (SMD) during rapid changes in meteorological conditions. This method provides more accuracy while reducing mean square errors (MSE). When compared to the SVR technique, this new algorithm gives better accuracy (R=96%) and lower MSE in ground moisture prediction. The hybrid learning approach for SVR+K-Means is utilised for irrigation planning since it has a greater accuracy and lower MSE. On the basis of agronomic knowledge, Goldstein *et al.* [8] developed cultivation recommendations. Gradient boosted regression trees (GBRT) was shown to be the best regression model solution for smart irrigation advice, with a precision of 93%. The agronomist may utilise the designed setup to regulate irrigation.

Roopaei *et al.* [9] suggested an intelligent monitoring method based on thermal imaging. Their study recommended using a thermal imaging sensor placed on a drone. The pictures generated by the imaging sensor are utilised to analyse crucial irrigation characteristics including as water demand, leaf quality, and fertiliser requirements. Acar *et al.* [10] used an extreme learning machine (ELM) based on a regression model to forecast soil moisture on the surface. The information gathered there is utilised to predict soil moisture content. Validation is carried by using a brand-new approach known as the “leave-one-out” cross endorsement method. The sine kernel function was used to assess the experimental setup, and the root-mean-square-error (RMSE) was discovered to be about 2.19 percent.

Wang *et al.* [11] suggested a method for analysing soil nutrient concentration in order to improve irrigation efficiency. They employed soft sensors based on ELM to calculate the generation of nutrient solutions. In the production of nutrient solutions, the method effectively tracks pH values, temperatures, and concentration fluctuations. Park *et al.* [12] forecasted soil moisture using soil moisture algorithms and MODIS data. The authors lowered the moisture level by using Random-Forest (RF) and cubist methods. An ensemble of these methods is used to acquire soil humidity data. The findings of their technique were compared to those of the least-squares method. Using machine learning techniques, Reda *et al.* [13] examined several approaches to assess soil organic carbon (SOC) and total-nitrogen (TN). To carry out their research, they took soil samples from four agricultural areas in the African nation of Morocco. Instead of employing traditional chemical soil analysis procedures, they used near-infrared (NIR) spectroscopy to gather data for their study. This method reduces the amount of time and other computing overheads. This method uses the ensemble learning modelling (ELM) technique to predict SOC and TN.

Morellos *et al.* [14] employed visible and near-infrared (NIR) spectroscopy to assess total nitrogen (TN), soil carbon, and humidity levels in an agricultural field. The spectroscopic dataset is used to estimate the three soil characteristics listed above. The predicted machine learning models are then built using these datasets. For the analysis, least squares support vector machines (LS-SVMs) and Cubist approaches were applied. Their findings demonstrated that the LS-SVM strategy is superior to linear-multivariate approaches for estimating soil parameters. Machine learning techniques were investigated by Mahmoudzadeh *et al.* [15] to estimate and forecast soil carbon concentration. They discovered that, in addition to SVM, KNN, Cubist, and extreme-gradient-boosting (XGBoost), RF accurately predictions SOC with R2 of 0.60 and RMSE of 0.30% on simulated data. SOC is influenced by air temperature, yearly rainfall, valley depth, and terrain roughness, according to the study. Veres *et al.* [16] investigated deep learning architectures, especially convolution neural networks (CNN) and conditional restricted Boltzmann machines, in order to predict soil properties using infrared spectroscopic findings. Stamenkovic *et al.* [17] proposed an SVR model for predicting soil moisture levels in remotely sensed hyperspectral images. Because the climate in this region varies throughout the year. Mohammadi *et al.* [18] used an extreme learning machine model to estimate daily water droplets and temperature in several sectors of Iran. Extreme learning machine models were shown to predict more correctly than SVM and ANN algorithms in the study is shown in Table 2 [19]-[27].

Table 2. Smart farming algorithms comparison

Smart farming approach	Attributes	Algorithms/approach
Affordable Smart Farming Using IoT and Machine Learning, Varghese and Sharma [3]	Soil, temperature, moisture	Linear regression (LR), SVM
Soil Moisture and Atmosphere Components Detection System Using IoT and Machine Learning, Anand *et al*. [4]	Humidity-temperature-moisture- rainfall	Hybrid approach MLR method and K-Means clustering
IoT based Smart Agriculture using Machine Learning, Reddy *et al.* [5]	Moisture, temperature and humidity	Decision tree
An IoT environmental data collection system for fungal detection in crop fields, Truong *et al.* [6]	Soil moisture – temperature - air humidity - wind speed - wind direction - sunlight intensity	SVMr
An IoT based smart irrigation management system using Machine learning and open source technologies, Goap *et al.* [7]	Soil moisture - temperature - climate conditions.	SVR and K-Means clustering
Applying machine learning on sensor data for irrigation recommendations: revealing the agronomist's tacit knowledge, Goldstein *et al.* [8]	Temperature - solar radiation - relative air humidity	GBRT, regression tree model (RTM), and boosted trees classifiers (BTC)
Machine learning based regression model for prediction of soil surface humidity over moderately vegetated fields, Acar *et al.* [10]	Soil surface moisture	Extreme learning machine regression (ELM-R)
Modeling of soft sensor based on DBN-ELM and its application in measurement of nutrient solution composition for soilless culture, Wang *et al.* [11]	pH value, temperature, and flow rate	ELM
AMSR2 soil moisture downscaling using multi sensor products through machine learning approach, Park *et al.* [12]	Soil moisture	RF and Cubist algorithms
A comparative study between a new method and other machine learning algorithms for soil organic carbon and total nitrogen prediction using near infrared spectroscopy, Reda *et al.* [13]	Soil organic carbon (SOC) and total nitrogen (TN)	Ensemble-learning algorithm
Machine learning based prediction of soil total nitrogen organic carbon and moisture content by using VIS-NIR spectroscopy, Morellos *et al.* [14]	TN, SOC, and moisture content (MC)	LS-SVM and Cubist ML algorithms
Spatial prediction of soil organic carbon using machine learning techniques in Western Iran, Mahmoudzadeh *et al.* [15]	Temperature, yearly rainfall	Cubist, XGBoost, RF, SVM, and KNN.
Deep learning architectures for soil property prediction, Vereset *et al.* [16]	Soil characteristics	Deep learning and CNN
Estimation of soil moisture from airborne hyperspectral imagery with support vector regression, Stamenkovic *et al.* [17]	Soil moisture	SVR
Improvement of crop production using recommender system by weather forecasts, Mohammadi *et al.* [18]	Daily water droplet point - temperature	ELM, SVM, and ANN

3. CONCLUSION

According to a recent World Health Organization study, approximately 800 million people (one out of every nine people) worldwide are hungry as a result of food shortages and poverty. Aside from this issue, the rapid growth in human population is another key element that contributes to food scarcity. Food scarcity is exacerbated by issues such as global warming, groundwater depletion, a lack of manpower in agriculture, pollution, and the shrinkage of agricultural area due to urbanisation and industrialisation. The necessity of producing and storing high-quality agricultural goods is highlighted by the aforementioned difficulties. These issues also point to the necessity for technical advancements in agriculture and farming. Smart farming has recently emerged as a viable method for producing high-quality agricultural products with low waste and human involvement. Machine learning, data analytics, cloud computing, and agricultural robotics are all examples of smart farming technology. These technologies help farmers from sowing to harvesting high-quality crops. This study provided a comprehensive overview of several smart farming architectures and algorithms. It has also emphasised the need of new technology in making farming smarter in order to fulfil future food demand and other demands. This report also concludes that additional research is required to make farming smarter in order to give high-quality food items to all living species, not just humans.

APPENDIX

Table 1. Sensors for smart farming

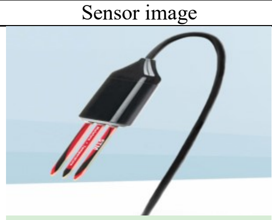
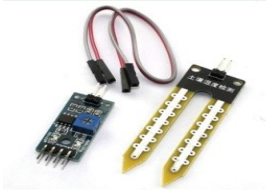
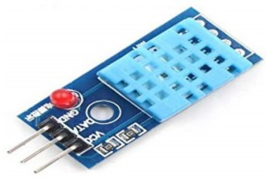
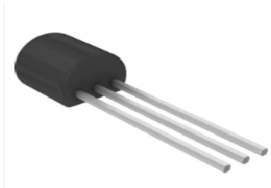
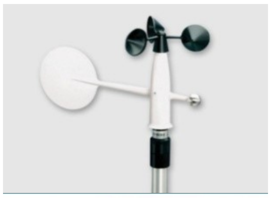
Sensor name	Details	Sensor image
Decagon ECH2O 5TM FDR sensor-frequency domain refractometry (FDR)	Measure the water level in the field	
GroPoint pro TDT sensor- time domain transmissiometry (TDT)	Measure the water level in the field	
Soil moisture sensor - soil hydrometer-humidity detector	Measure the amount of humidity in the soil	
DHT11 - temprature and humidity sensor module	Measure the amount of humidity and temperature in the Environment	
LM35DZ/LFT1 temperature sensor analog	Measure the amount of temperature in the Environment	
Water-level-sensor	Measure the depth of the water level	
DN25 1inch water flow sensor	Measure velocity variations at varying flow speeds. The sensor with hall effect transmits the appropriate signal.	
PROD-WM30-1280x960	Measure wind direction and measure wind speed.	
MQ135 - air quality gas sensor	Sensor for air quality to track a variety of gases like NH3, NOx, alcohol, benzene, smoke, and CO2.	

Table 1. Sensors for smart farming (continue)

Sensor name	Details	Sensor image
Pollution monitoring module ZP07-MP503 - 5V air quality sensor module	For detecting chemical reactive gases, e.g. formaldehyde, benzene, carbon monoxide, ammonia, hydrogen, alcohol and smoke and so on.	
Rain drop sensor module	Rain sensor or detector module for rain detector is easy and convenient to use. When rain hits on the sensor, the module acts like a switch. It also tests rain intensity	

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